Identification of Gait Events combining Bayesian Hidden Markov Models and Linear Regression

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Abstract— **The Hidden Markov Model is a probabilistic time-series model that has recently found application in human motion analysis. HMMs are usually fit directly to time-series data obtained from motion capture systems, using Gaussian observation models and the Expectation Maximization algorithm. The boundaries of the segmentation induced by the HMM are somewhat arbitrary, because the motion capture data usually consists of smooth trajectories. When *a-priori* segmentation is available, like in the case of clinically defined events in human gait, biasing the HMM parameters towards this prior knowledge is crucial to obtain a segmentation that is clinically relevant. To achieve this goal, we propose the combination of a fully Bayesian HMM with a sliding-window polynomial fit pre-processing step. In the context of automatic segmentation of gait time-series, we show how the proposed approach allows to better exploit *a-priori* segmentation, and to learn a set of motion primitives that improve the segmentation performances over classical HMMs.**

I. MOTIVATION

Three-dimensional Gait Analysis (3DGA) is a tool for the clinical assessment of a patient's gait through the observation of joint angles trajectories obtained using a motion capture system. Each human gait cycle can be described as a sequence of phases, delimited by clinically defined gait events, shown in Figure 1. The segmentation of the joint angles time-series based on the gait events is relevant for clinical assessment, and is often performed manually. There is therefore an interest in developing an automatic segmentation approach that is able to identify gait events from previously observed gait time-series. While proposing a solution to this problem, we raise the attention to two development directions for further application of HMMs in human motion analysis, namely increasing the set of *motion primitives* to segment human motion beyond the simple Gaussian model, and move towards *fully Bayesian* learning of the HMM parameters in order to exploit domain specific knowledge during model fitting.

II. METHODS

Hidden Markov Models (HMMs) [1] are one of the simplest probabilistic time-series model and they have recently found application in human motion analysis for humanoid robot motion generation [2], [3], robot programming by demonstration [4], human motion segmentation [5] and rehabilitation [6], [7].

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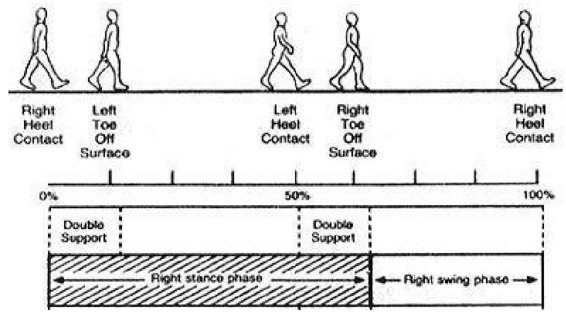

Fig. 1: Gait cycle phases

The HMM can be seen as a stochastic finite state automaton, where at each time t an *hidden* state h emits an observation y . Assuming that the observation follow a Gaussian distribution, the HMM is defined by the parameters $\lambda = \{\mathbf{A}, \mathcal{N}(\mu_s, \Sigma_s), \pi\}$, where π is the initial distribution of the state, $\mathbf{A}$ is the transition matrix encoding its Markovian dynamic, and $\mu_\mathbf{s}$ and Σ_s represent the mean and the covariance of the Gaussian observation model associated with each state $s \in \{1 \dots S\}$. An HMM induces a segmentation of the time-series whose boundaries are influenced by the chosen observation models and the learning routine. A common choice when no *a-priori* segmentation is available is the Gaussian observation model and the Expectation Maximization (EM) algorithm for learning. The number of states is typically chosen via model cross-validation. In our application, we focus on ankle joint time-series during stance phase. Our dataset is composed of 40 time-series consisting of 180 points, shown in Figure 2 together with the *a-priori* segmentation, given by the toe-off and heel contact events for the two feet. Before fitting the HMM, we perform linear regression to fit third order polynomial function to the observations contained in a sliding window of size 15. This process results in a four dimensional time-series of the computed regression coefficients. The idea is to fit an HMM with Gaussian observation models to these latter time series, rather than directly on the observations. In this way, each state of the HMM is associated to a cluster of regression parameters that follows a Gaussian distribution. Therefore, each state encodes a polynomial *motion primitive*, that is able to model the variability in the data trough the covariance of the Gaussian distribution. We chose a Bayesian approach to fit and HMM to the regression parameter time-series, namely the Hierarchical Dirichlet Process HMM (HDP-HMM) [8]. This fully Bayesian approach allows to specify prior distribution for all the HMM parameters, and to obtain

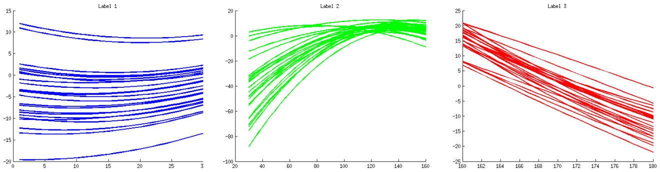

Fig. 3: Learned motion primitives obtained sampling from the regression parameter posterior distribution

posterior estimated from data using Markov Chain Monte Carlo sampling. The prior distributions on the observation models can be specified providing pre-segmented time-series. These priors are obtained conditioning a vague prior on the observation contained in each segment. In this way, before segmenting a new time-series, the HMM contains already a set of previously observed *motion primitives*. In the HDP-HMM setting, the number of hidden states is estimated automatically. In our application, we set the number of states to three, because it corresponds to the phases in the gait the we are trying to segment. To demonstrate the effectiveness of our approach, we also fit a classical model, where the HDP-HMM is fit directly to the joint angle time-series data, rather than on the regression coefficient time-series. We use the segmentation of 20 time-series to initialize the prior for the observation models, and we fit the HDP-HMM to the remaining 20 and we compare the obtained segmentations with the ground truth ones.

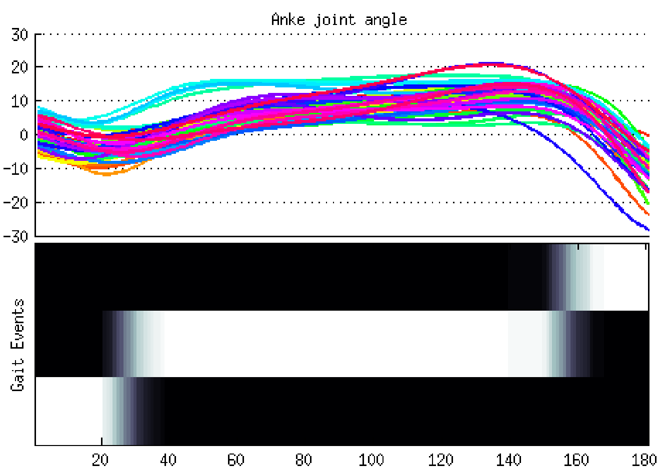

Fig. 2: Time-series of ankle joint during stance phase and corresponding ground truth segmentation

III. RESULTS

To evaluate the segmentation performance, we use the Normalized Hamming distance between the estimated segmentation labels and the ground truth ones, as suggested in [8]. The overall Hamming distance obtained using the classical HMM is 25.7% while the one using the polynomial sliding window is 9.8%. This can be explained by the fact that the polynomial fit observation models better represent the motion primitives delimited by the gait events, as visible in Figure 3, where for each label we draw samples from the regression parameter distributions and plotted the corresponding time-series . Using the available segmentation to inform the prior distribution on the observation models, allows the HMM to encode the *shape* of the motion primitives in the gait and to segment the time series accordingly.

IV. CONTRIBUTION TO THE WORKSHOP

In this short paper we have shown a variant of the classical HMM that segment human motion time series in clinically relevant motion primitives. While the polynomial fit is performed as a separate pre-processing steps on a fixed size sliding window, the HDP-HMM can in principle solve the linear regression and the segmentation problem concurrently. This opens the possibility to develop a wide family of *motion primitives* using combination of linear kernels. The development of new learning approaches for fully Bayesian time-series models is hot topic in the Machine Learning community. Inference and learning tools become faster and more accurate everyday, and recent models allow to incorporate prior knowledge on state durations [9], split the time-series in switching state space models [8], or to combine simpler models in a factorial fashion. We believe that these methods find in human motion analysis an ideal application, due to the amount of expert knowledge that can be leveraged using the Bayesian framework. How to use this models to solve relevant problems in human motion understanding and how express the domain specific knowledge in informative priors remains on open and exciting challenge.

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